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A CROSS-ASSET MANAGEMENT FOR TRANSPORTATION INFRASTRUCTURE SYSTEMS

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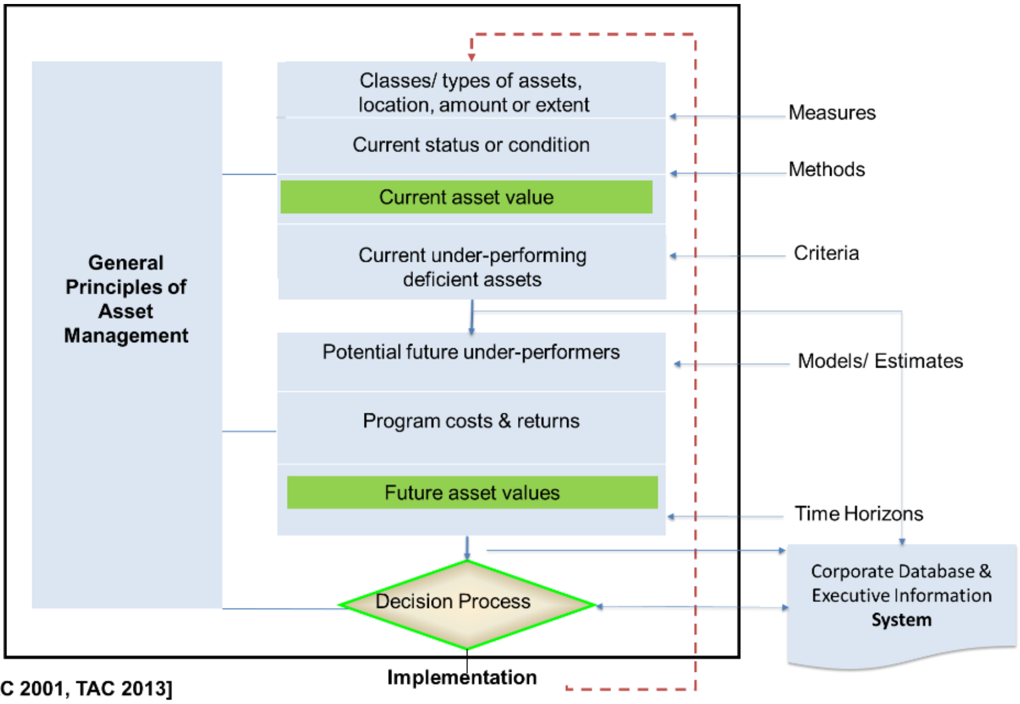
Abstract: Transportation infrastructure systems are pillars for society development and growth. The challenge of fund limitation, aging, and deteriorating infrastructure, and higher loading demand increase the mandate for implementing effective asset management to manage transportation infrastructure assets cost effectively at acceptable levels of service. Pavement and Bridge Management Systems have existed for several years. However, these systems are often operated separately. Agencies are faced with the challenge of fund allocation and the trade-off between assets. Therefore, there is a need for a decision support system that cost-effectively optimizes the trade-off between systems' components; for example, allocating funds for bridge rehabilitation or pavement rehabilitation while deferring the other. On the other hand, there is a unique advantage in cross-asset optimization in that cost saving can be generated through bundling of asset components by location for maintenance and rehabilitation. In essence, cross-asset management provides opportunities to reduce procurement cost, user delay, and interruption. This paper presents a cross-asset management methodology using hazard and survival model. A case study is presented to demonstrate the proposed methodology.

1 Introduction

Asset Management in basic terms is a systematic business process that employs strategic, engineering and economical means to provide a holistic approach to managing infrastructure assets to meet specified performance measures' level of services. There are many definitions of Asset Management in the literature; however, a widely used definition is the one proposed by the Federal Highway Administration (FHWA) US Department of Transportation (FHWA 1999) also adopted by Transportation Association Canada (TAC) (TAC 2013) "*Asset management is a systematic process of maintaining, upgrading and operating physical assets cost-effectively. It combines sound business practices and economic theory, and it provides tools to facilitate a more organized logical approach to decision making. Thus, asset management provides a framework for handling both short- and long-range planning.*" Asset management can be viewed as a strategic system into which all network management systems feed to (TAC 2013). A widely used asset management framework is illustrated in TAC pavement design and management guide (Figure 1) (TAC 2013).



[TAC 2001, TAC 2013]

Figure 1: Overview framework for asset management

Although there is a common framework for asset management, transportation agencies have traditionally made investment decisions for individual assets separately. Independent management systems have indeed traditionally been developed to manage pavements and bridges, the two main transportation assets. Therefore, Pavement Management Systems (PMSs) and Bridge Management Systems (BMSs) are often operated separately. This lack of integration between management systems may be due to restrictions associated with funding and/or limitations to the agency's ability to compare data objectively across asset types (Proctor and Zimmerman 2015). Deciding how best to allocate limited resources across these various asset classes to provide acceptable performance poses a persistent and difficult challenge for agencies.

A recent report published by AASHTO (Proctor and Zimmerman 2015) identified three levels of cross-asset management that differ in their complexity and quantified sophistication: cross-asset trade-offs, cross-asset allocation, and cross-asset optimization. Cross-asset trade-offs represent the simplest and most common of the three concepts. Under this approach, resources are transferred between asset classes in order to maximize perceived utility (Proctor and Zimmerman 2015). In this definition is important to highlight that utility is perceived and not measured nor quantified. This means that although cross-asset trade-offs can be data-driven, it is somewhat informal and dependent upon the judgment of a few individuals (Proctor and Zimmerman 2015). Cross-asset allocation is the next most sophisticated decision process, as it relies on a simultaneous quantification of benefits of asset classes (Proctor and Zimmerman 2015). Under this approach, all the investment candidates in the different asset classes will be assessed and ranked using a common benefit indicator. Some of the indicators that could be used in this evaluation are benefit/cost ratio, multi-criteria decision analysis and risk/reward-based allocation (Proctor and Zimmerman 2015). Finally, cross-asset optimization represents a further refinement of cross-asset allocation. By using recursive mathematical computations, cross-asset optimization determines the maximum utility for a given set of investments constrained by a set of performance parameters (Proctor and Zimmerman 2015).

Previous studies have attempted to analyze different approaches for optimal cross-asset allocation. Fwa and Farhan (2012) proposed a two-stage optimization process. In the first stage, an individual asset system optimization was performed searching minimal maintenance cost for each asset class. The set of solutions obtained for each asset class will then be considered in a second optimization stage dealing with the cross-asset allocation. The objective of the second optimization stage is to achieve an equitable allocation of the budget by maintaining equivalent amounts of performance improvements between asset classes. In this two-stages optimization, Fwa and Farhan (2012) considered different performance indexes for each asset class (e.g. PCI for pavements and BHI for bridges) and searched for an equitable allocation of the budget by minimizing the gap between each asset class condition and their threshold performance. Dehghani et al. (2013) proposed a cross-asset resource allocation framework that considers functional, structural and environmental performance indicators to estimate the optimal budget to invest in each asset. When applying this framework, Dehghani et al. (2013) found that the weights assigned to each indicator changed the optimal resource allocation. Wang and Chou (2015) proposed an optimization model considering integer and constraint programming aimed to optimize project scheduling by coordinating projects among different assets. In this application, the objective was to maximize the total benefits of the projects, assessed in terms of the asset condition and the vehicle operating cost. In order to integrate different assets in this optimization process, Wang and Chou (2015) considered a common condition index based on a five-point scale, named asset condition index (ACI) for all the asset classes. The main limitation of implementing this approach is that transportation agencies are currently using different and independent performance indexes for each asset class.

1.1 Problem Statement

The studies presented thus far provide evidence that one of the key aspects of cross-asset management is how to assess the performance of different asset classes using a common indicator. Different assets often have independent sets of performance measures so there is a need to adopt a common performance measure to capture the effect of each project’s implementation in the cross-asset optimization process.

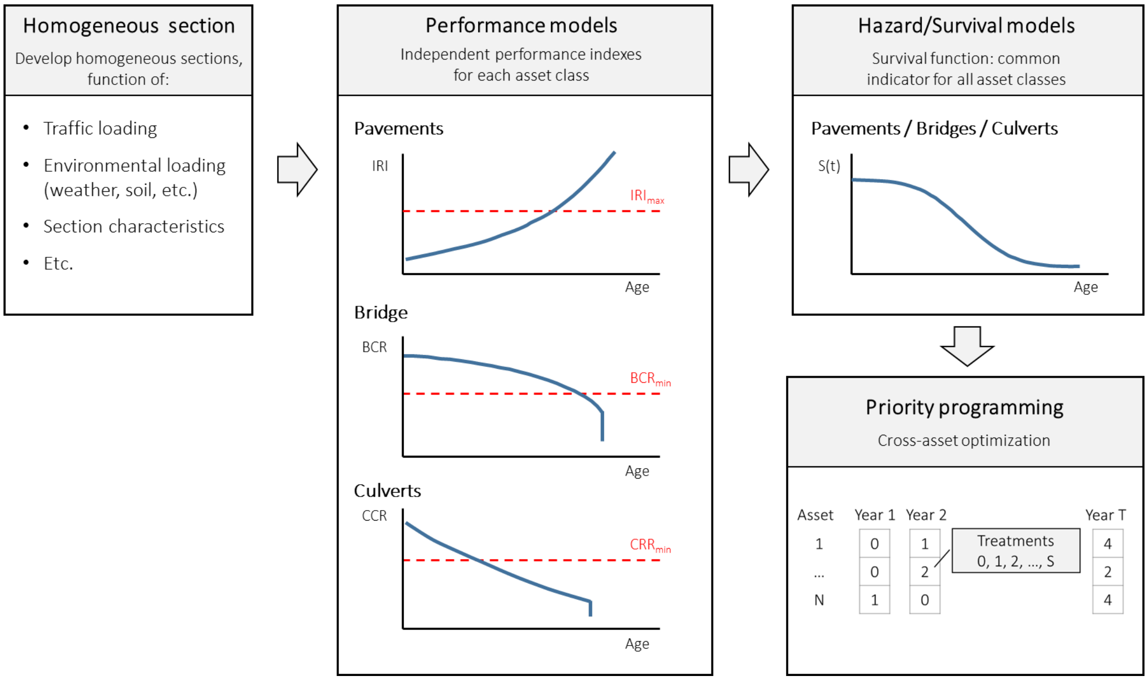
1.2 Scope and Objective

In order to cover this gap, this paper proposes a framework for cross-asset management of transportation systems using hazard models. By using hazard models, the proposed framework allows incorporating the risk of performance failure due to aging infrastructure and lack of maintenance or rehabilitation.

The objective of this research is to develop a framework for the cross-asset management of transportation systems based on hazard models. The present study extends the traditional cross-asset management framework by applying a common methodology (hazard/survival models) to predict assets service life. The proposed framework will help infrastructure managers in the allocation of resources across different assets and document investment trade-offs between asset classes. By using the proposed tool, transportation agencies will be able to demonstrate how priorities and performance objectives drive decision-making.

2 Proposed Framework

The proposed framework for cross-asset optimization consists of three modules (Figure 2): performance models, hazard/survival models, and priority programming. The first module corresponds to traditional deterioration models performed by independent management systems. These models describe the deterioration of each asset class using different performance indexes. In order to have a common indicator of all asset classes, the proposed framework develop hazard/survival models for each asset class. The survival functions obtained from this module allow to perform cross-asset optimization using a common indicator for all asset classes. Each of these modules are described in detail in the sections below.



Asset	Year 1	Year 2	Year T
1	0	1	4
...	0	2	2
N	1	0	4

Figure 2: Proposed framework for cross-asset management

2.1 Performance Models

Performance modeling is used to predict performance and deterioration of assets as a function of time, and therefore, predict the service life of assets. Asset performance is assessed in terms of an indicator that evaluates the degree to which the infrastructure serves its users and fulfills the purpose for which it was built or acquired (Uddin et al. 2013). Various types of distress, such as roughness, rutting, etc., or indexes based on combinations of such distresses such as Bridge Health Index (BHI), Pavement Condition Index (PCI), etc. can be used as performance indicators for these models (FHWA 2002).

Performance models are a key element for the development of multi-year maintenance programs, as they allow to understand the current condition of the complete network but also to understand how asset condition will change over time (TAC 2013). Figure 3 illustrates how performance modeling is used to predict future deterioration of pavement, expected improvements due to the application of maintenance or rehabilitation activity and determining the “need year” of application.

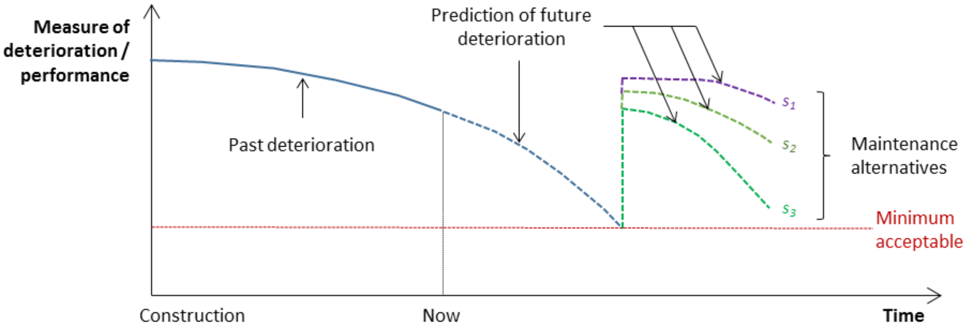


Figure 3: Deterioration Modeling and Impact of Maintenance Activities (FHWA 2002)

Asset deterioration process is affected by many factors such as environment, loading, and material. Therefore, to construct accurate deterioration models for maintenance and rehabilitation activities, homogeneous sections should be identified (Alyami and Tighe 2013). For each asset category, homogenous families are grouped and deterioration models are developed as an input to constructing survival models.

2.2 Hazard/Survival Models

Survival analysis and hazard-based duration models are methods that can estimate the probability of survival and failure of a specific asset in certain age. Some previous studies have used these models to analyze asset deterioration and failure (Nakat and Madanat 2008; Gao et al. 2012; Anastasopoulos and Mannering 2015; Chen et al. 2015).

The first step of hazard-based duration model is to develop the cumulative density function (CDF),

[1] $$F(t) = P(T < t)$$

where *P* is probability, *T* is time, and *t* is some specified time. The probability density function of this CDF is,

[2] $$f(t) = \frac{dF(t)}{dt}$$

Hazard-based duration models could estimate the conditional probability of the asset service life ending at time *t* (it is assumed that the service life was not ended until time *t*). The probability of failure is significantly important because if this probability increases, the asset service life would also increase (Anastasopoulos and Mannering 2015). The hazard function can be written as,

[3] $$h(t) = \frac{f(t)}{1-F(t)}$$

where *f(t)* and *F(t)* are the probability density function and cumulative probability distribution function, respectively. Hazard function presents the probability in which the asset service life ends at time *t*, if it was not ended before time *t*. Based on this conditional probability function, the $H(t)$ could be estimated. $H(t)$ is the cumulative hazard function and provides the summation of probabilities at which events are ending up to or before time *t*. This integrated function can be written as,

[4] $$H(t) = \int_0^t h(t)dt$$

Survival functions presents the probability of an asset will survive beyond a specified time. This function could be formulated as,

[5] $$S(t) = EXP\big(-H(t)\big)$$

The most common parametric hazard-based duration methods involve Exponential, Weibull, and log logistic models. Weibull models were used for this study, which can be expressed as,

[6] $$h(t) = \lambda p(\lambda t)^{p-1}$$

where $\lambda > 0$ is scale parameter and $p > 0$ is shape parameter. $H(t)$ and $S(t)$ for Weibull distribution can be written as,

[7] $$H(t) = (\lambda t)^p$$

[8] $$S(t) = EXP(-(\lambda t)^p)$$

Developed survival models for each asset presents the probability of that asset to survive beyond a specific time. This means that there is an opportunity to estimate the survival rate in each year and choose the assets with the lowest probability of survival for the trade-off between major maintenance or rehabilitation among different assets. This approach also aims to group various assets which are locating in same or closer sections. In other words, using the survival probabilities, assets can be moved or delayed to be grouped with another within the same section in order to reduce the number of lane closures and service interruptions during multiple years, potentially reduce the procurement and overall costs, and improve the overall network condition.

2.3 Priority Programming

The optimal design of maintenance programs is not straightforward. Indeed, it presents S^{TxN} possible solutions in a network with N assets, S possible maintenance treatments over a planning horizon of T years (Golroo and Tighe 2012; Yepes et al. 2016). Selection of maintenance and rehabilitation alternatives can be based on engineering judgment, local experience or agencies policies (TAC 2013). In transportation management systems, priority programing involves four steps: integrating information, identification of needs, priority analysis, and output reports (Alyami 2012). Various priority programming methods are established ranging from simple to more complex mathematical programming (Haas et al. 1994).

In broad terms, techniques used in asset management for priority programming can be classified in three groups (Torres-Machi et al. 2014): selection based on ranking, mathematical optimization methods and near optimization methods. Selection based on ranking is performed by enlisting and rating alternatives based on an indicator. This indicator can be based on judgment, pavement condition or economic analysis. This method is easy to understand but it can only be used when the number of alternatives is limited (Zimmerman 1995; Meneses and Ferreira 2013).

Mathematical optimization methods select alternatives maximizing or minimizing an objective function while satisfying some constraints. Objective functions commonly considered are: maintenance costs, vehicle operating costs and effectiveness, among others. Mathematical programming methods commonly used for infrastructure asset management are: linear, nonlinear, integer and dynamic programming. Compared to ranking, mathematical optimization methods present the advantage of providing optimal solutions. However, they are not suited to deal with large networks because the complexity of the problem increases, requiring long computing time (Torres-Machi et al. 2014).

Near optimization methods, also called heuristic methods, give solutions that are close approximations to those derived from mathematical optimization. Heuristic methods, whose development is linked to the evolution of artificial intelligence procedures, include a large number of search algorithms based on iterations in which the objective function is evaluated and the constraints are checked (Yepes et al. 2016). Previous studies have reported that heuristic methods lead to simpler and more computationally efficient solutions than mathematical methods (Ferreira et al. 2002).

The selection of the most appropriate method for priority programming depends on the characteristics of the problem. Whereas simple methods such as priority based on ranking can be used when the number of alternatives under evaluation is low, more sophisticated methods such as heuristic methods may be recommended for higher asset networks.

3 Case Study

An illustrative application of the proposed framework for the cross-asset management of transportation infrastructures is presented in this section. The case study consists of an infrastructure transportation system which was part of an asset management challenge posted at the 7th International Conference on Managing Pavements (Haas 2008; Saad 2014). The network of assets is composed of pavements, bridges, and culverts.

The pavement network is comprised a total of 1,293 road sections with a total length of 3,240 km. Two types of road sections were considered: interurban and rural. The former is represented on the medium to very highly trafficked roads, while the latter spans most traffic and condition categories. The information given on each road section includes: length, width, Annual Average Daily Traffic (AADT), year of construction, and surface condition (International Roughness Index, IRI; Pavement Quality Index, PQI; Surface Distress Index, SDI; etc.) Other general information was also given, regarding the annual rate or

IRI increase; the maximum allowed IRI value; and the unit cost of pavement maintenance and rehabilitation treatments.

The bridge component is comprised 161 bridges. Two types of major structures were considered in this analysis: concrete and steel. The information given on each bridge includes: length, number of spans, maximum span length, span type, clear roadway width, skew angle, usage, first year in service, and load capacity. Information regarding condition is also included in terms of a condition rating, sufficiency rating, and replacement cost.

The culvert component of the transportation system is comprised 356 culverts. Information provided for each culvert includes: maximum diameter, span type, clear roadway width, skew angle, and first year in service. Similarly, the replacement cost, condition rating, and sufficiency rating for each culvert is provided.

As indicated, for each asset category, homogenous families are grouped and deterioration models are developed as an input to constructing survival models following the steps indicated in section 2.2. For example, homogeneous road sections were classified in four categories of traffic level: rural low traffic, rural medium traffic, interurban high traffic, and interurban very high traffic. Table 1 summarizes the information considered for the development of hazard models and survival functions for each asset class. Table 2 shows the parameters of the survival functions obtained for each asset. Figure 4 shows an example of the survival function obtained for steel major bridges.

Table 1: Information considered for the development of hazard/survival models

Asset class			Trigger level
Pavement	Rural	low traffic (AADT < 1,500)	IRI ≥ 2.8 mm/m
		high traffic (AADT > 1,500)	IRI ≥ 2.3 mm/m
	Interurban	low traffic (AADT < 8,000)	IRI ≥ 2.2 mm/m
		high traffic (AADT > 8,000)	IRI ≥ 1.9 mm/m
Bridge	Concrete		Condition rate < 70
	Steel		Condition rate < 60
Culvert	N/A		Condition rate < 70

Table 2: Parameters of the survival functions for each asset class

Asset class			λ	p
Road	Rural	Low traffic (RRLT)	0.133	5.632
		High traffic (RRMT)	0.142	5.357
	Interurban	Low traffic (RIHT)	0.084	1.634
		High traffic (RIVHT)	0.115	6.105
Bridge	Concrete (BC)		0.023	9.865
	Steel (BS)		0.024	5.642
Culvert	Culvert (C)		0.021	4.295

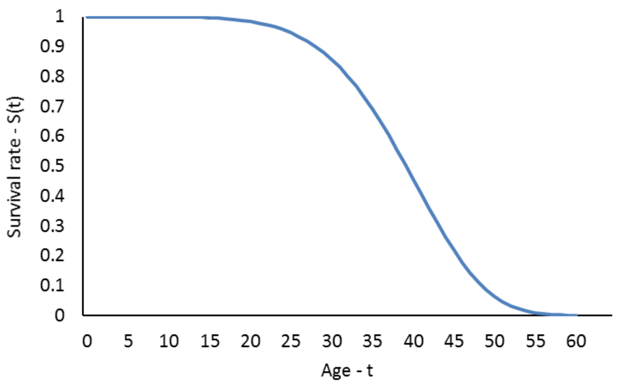
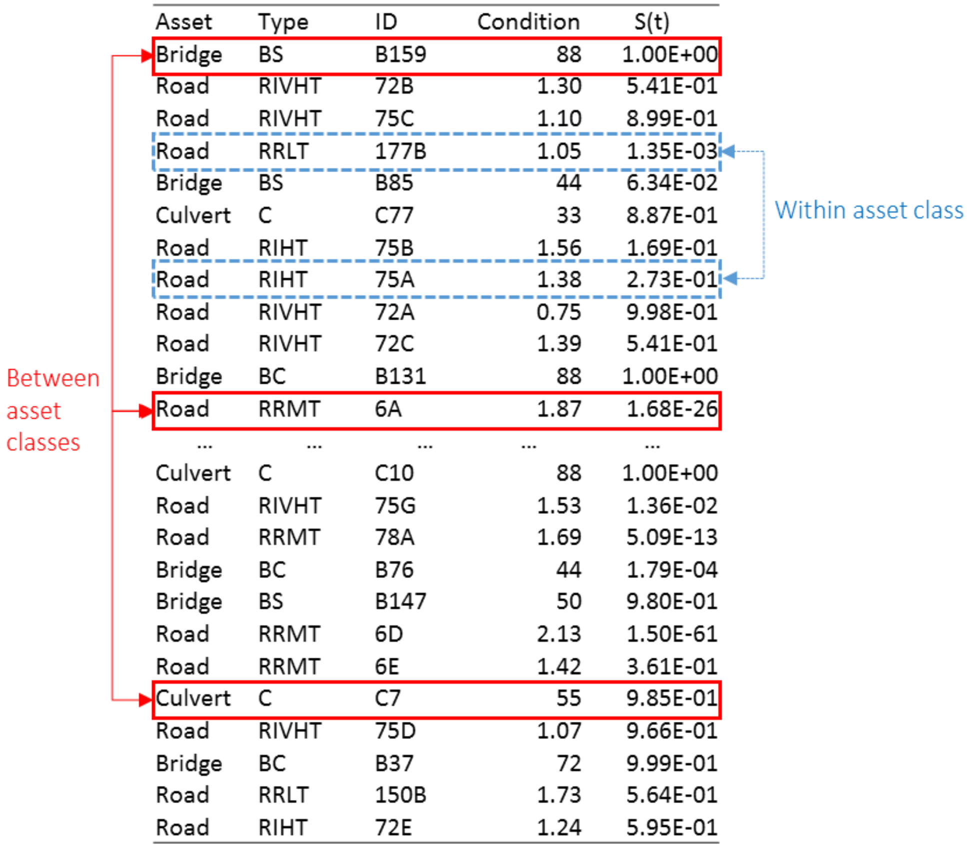


Figure 4: Survival function obtained for steel major bridges

In order to analyze the capabilities of the proposed framework, an example of cross-asset priority programming is shown in Figure 5. The use of the proposed survival functions allows to compare the need of maintenance both within asset class and between asset classes. Because S(t) accounts for the probability of survival, assets with lower value of S(t) have a higher need or priority. Therefore, from the example shown in Figure 5, it could be observed that within road assets, road 177B presents higher risk of failure and therefore higher need of maintenance than road 75A. Similarly, an analysis of maintenance need between asset classes can be performed based on S(t). In this case, when comparing the maintenance need of bridge B159, road 6A and culvert C7, the proposed framework allows to determine that the highest priority should be given to road 6A, followed by culvert C7 and bridge B159.



Asset	Type	ID	Condition	S(t)
Bridge	BS	B159	88	1.00E+00
Road	RIVHT	72B	1.30	5.41E-01
Road	RIVHT	75C	1.10	8.99E-01
Road	RRLT	177B	1.05	1.35E-03
Bridge	BS	B85	44	6.34E-02
Culvert	C	C77	33	8.87E-01
Road	RIHT	75B	1.56	1.69E-01
Road	RIHT	75A	1.38	2.73E-01
Road	RIVHT	72A	0.75	9.98E-01
Road	RIVHT	72C	1.39	5.41E-01
Bridge	BC	B131	88	1.00E+00
Road	RRMT	6A	1.87	1.68E-26
...	...	...	...	...
Culvert	C	C10	88	1.00E+00
Road	RIVHT	75G	1.53	1.36E-02
Road	RRMT	78A	1.69	5.09E-13
Bridge	BC	B76	44	1.79E-04
Bridge	BS	B147	50	9.80E-01
Road	RRMT	6D	2.13	1.50E-61
Road	RRMT	6E	1.42	3.61E-01
Culvert	C	C7	55	9.85E-01
Road	RIVHT	75D	1.07	9.66E-01
Bridge	BC	B37	72	9.99E-01
Road	RRLT	150B	1.73	5.64E-01
Road	RIHT	72E	1.24	5.95E-01

Figure 5: Cross-asset priority programming

From the illustrative case study shown above it can be concluded that the proposed framework allows to perform cross-asset priority programming using a common indicator for all the asset classes. Further work is required to investigate the implementation of optimization techniques for the priority programming.

4 Conclusions

This paper presents a framework for cross-asset management of transportation infrastructure systems based on hazard/survival models. For illustrative purposes, the proposed framework was applied to a case study consisting of an infrastructure transportation system which included pavements, bridges, and culverts. From this application it can be concluded that:

- The proposed framework allows to compare the maintenance and rehabilitation needs of different asset classes using a common indicator based on survival functions. The proposed model indicates the probability of survival of a given asset, at any given year, to meet the required level of service.
- By using hazard models, the proposed framework allows incorporating the risk of structural performance failure due to aging infrastructure and lack of maintenance or rehabilitation impact on the network. This concept aligns with agencies' direction towards risk-based asset management, such as MAP-21 requirements.
- The proposed model allows for investment trade-off analysis between assets, taken into account the system risk of failure and survival to meet the required level of service.

Although the proposed work is demonstrated through the case study, future work include:

- A comparison of the proposed model results to other models proposed in the literature.
- A sensitivity analysis to determine the need of a weighting system between asset types and the improvement achieve among asset groups.
- An exploration of different optimization techniques for cross-asset budget allocation that will enhance the solutions provided by ranking.

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